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A Novel Approach for Detection of Adaptive Vehicle in Complex Environmental Fields

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ABSTRACT—*This paper proposes methods for identifying the vehicle in traffic jams and in complex weather conditions. In recent research, there have been many well-known vehicle detectors that utilize background extraction methods to recognize vehicles. In these studies, the background image needs to continuously be updated; otherwise, the luminance variation will impact the detection quality. The vehicle detection under various environments will have many difficulties such as illumination vibrations, shadow effects, and vehicle overlapping problems that appear in traffic jams. The main contribution of this paper is to propose an adaptive vehicle detection approach in complex environments to directly detect vehicles without extracting and updating a reference background image in complex environments. In the proposed approach, histogram extension addresses the removal of the effects of weather and light impact. The gray-level differential value method is utilized to directly extract moving objects from the images. Finally, tracking and error compensation are applied to refine the target tracking quality. In addition, many useful traffic parameters are evaluated.*

Index Terms: *Histogram extension (HE), tracking, traffic jam, tracking compensation, vehicle detection.*

I. INTRODUCTION

WITH the growing number of vehicles, traffic information increasingly becomes important for drivers. Many approaches have been proposed for tackling related problems in intelligent transportation system (ITS). A joint random field (JRF) model for moving vehicle detection in video sequences. The proposed method could handle moving cast shadows, lights, and various weather conditions. However, the method did not recognize vehicle classification and velocity. Vehicle detection approach for detecting vehicles from static images using color and edges. This method introduced a new color transform model to find important "vehicle colour" for quickly locating possible vehicle candidates. This method could also detect vehicles in various weather conditions, but it did not address resolutions on traffic jams and shadow reduction. The multilevel framework to detect and handle vehicle occlusion. The proposed framework consisted of intraframe, interframe, and tracking levels to resolve the occluded vehicles. The method for segmenting and tracking vehicles on highways using a camera that was relatively low. A low-level object tracking system that produced accurate vehicle motion trajectories, which could further be analyzed to detect lane centers and classify lane types. A lane-detection method that was aimed at handling moving vehicles in traffic scenes. A new background subtraction algorithm based on the sigma–delta filter, which was intended to be used in urban traffic scenes. An example-based algorithm for moving vehicle detection. The model based approach uses a 3-D model to detect vehicles. Inthis method, different models that correspond to different types of vehicles are created. In this method, the vehicles could easily be tracked, and computation loading could significantly be reduced. A vision-based system with gradient operator to detect sub corner features of the vehicles and grouped these features to detect the vehicles. The advantage of this method was that it was less sensitive to change in illumination. An integrated moving edge detection and headlight detection into a hybrid system. This system worked not only during the day but also at night. Unlike most methods referring to background image, they used a three-image difference to detect moving edge. This method reduced both the dependence on background and the time of background learning. However, noise affected the system to a great extent. Background segmentation was one approach for extracting the common part between different images in a frame. A vehicle-tracking algorithm to estimate traffic parameters using corner features. A 3-D model matching scheme to classify vehicles into various types, such as wagons, sedan, and hatchback. A region-based approach to track and classify vehicles based on the establishment of correspondences between regions and vehicles. A manual method of camera calibration has been presented to identify lane locations and corresponding lane widths. Finally, many recent ITS-related studies have been proposed .A case study where the objective was to identify the optimal subset of routes for real-time traveller information in a highway network. A privacy aware monitoring system (PAMS) that worked as an aggregate query processor that protected the location privacy of drivers as it made the IDs of cars

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anonymous. A regulator to track the optimal vehicle-detector location in a variety of traffic conditions and an algorithm to adjust the detected data from the original fixed detector as if they were detected by the detector at its time-dependent optimal location. An overview of the background, concepts, basic methods, major issues, and current applications of parallel transportation management systems (PtMS).A queuing network-based computational model to explain driver performance in a pedestrian-detectiont ask assisted with night vision enhancement systems. A novel approach to vision-based road detection that was robust to shadows. Although there were many studies on vehicle detection, few research proposed methods for solving problems of detecting vehicles in various complex environments, particularly in trafficjams that frequently occur in practical traffic conditions. The vehicle detection under various environments will meet many difficulties such as illumination vibrations, shadow effects and vehicle overlapping problems that appear in traffic jams. In this paper, an adaptive vehicle detection approach for complex environments is proposed for solving problems of vehicle detection in traffic jams and complex weather conditions like sunny days, rainy days, sunrise, sunset, cloudy days, fog, or atnight. Histogram extension (HE) addresses how we can remove effects of weather and light impact. The gray-level differential value method (GDVM) is used to dynamically segment moving objects. Finally, tracking and error compensation are applied to refine the target tracking quality. In addition, many usefu l traffic parameters are evaluated from the proposed approach, including traffic flows, velocity, and vehicle classifications.

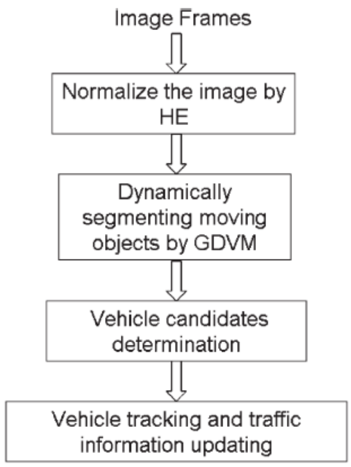

Fig. 1.System overview of the proposed approach.

Fig. 2.Source image and its ROI.

These useful parameters can help in controlling traffic and provide drivers good driving guidance. This paper is organized as follows. Section II addresses the system overview. Section III shows the HE method, which makes images from various environments similar to each other.

II. SYSTEM OVERVIEW

Fig. 1 shows the system overview of the proposed approach. There are several steps in the flowchart. First, images are normalized by HE. Second, moving objects are dynamically segmented by GDVM. Next, vehicle candidate detection, vehicle tracking, and error compensation are applied. Finally, the traffic parameters are evaluated and updated. To reduce computing loads, all algorithms are applied only in the region of interest (ROI), as shown in Fig. 2. In the proposed system, a monocamera is installed to capture the full color images. The viewing angle is the front view. The camera has fixed height and viewing angle.

III. HISTOGRAM EXTENSION

Input image frames in various environments have various properties. These fluttering properties may damage the detection quality. In practical conditions, a vehicle detection system must work well in all kinds of complex environments. Different environments produce different light effects that make vehicle detection hard to work well.

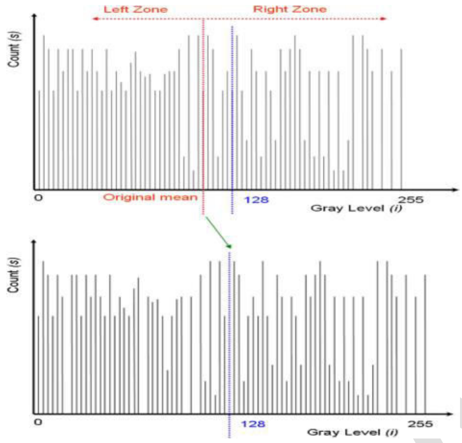

Fig. 3.LNMS.

Histogram extension (HE) is a method that removes the effects of weather and light impact. The first step for the HE method is to decompose a truecolor image into its red–green–blue (RGB) components and calculate the histogram in the ROI for each component. Next, linear normalization with mean shift (LNMS) is applied to normalize the source images. There are several steps for the LNMS method. First, the original mean value of all pixels, denoted as *mp* in (1), shown below, is shifted to 128. Next, α and β, which are defined as shifting parameters in (2), shown below, are calculated for the left and right zones, respectively, as shown in Fig. 3. Finally, all gray levels that correspond to gray-level counts, denoted as $iL(s)$ in the left zone and $iR(s)$ in the right zone, are normalized to the new ones, denoted as $niL(s)$ and $niR(s)$. In (3), shown below, $iL(s)$ is the original gray level that corresponds to the gray-level count in the left zone, $iR(s)$ is the original gray level that corresponds to thegray-level count in the right zone, $niL(s)$ is the shifted gray level that corresponds to the gray-level count in the left zone,and$niR(s)$ is the shifted gray level that corresponds to the graylevelcount in the right zone. We have where $i$is the gray-level value, and $s(i)$ is the pixel count in gray level i. In addition

$$\alpha = \frac{128}{m_p} \qquad \beta = \frac{128}{255 - m_p}$$

When LNMS is applied to each component of RGB, the new mean values of R, G, and B will approach 128. In addition, the gray-level scale in the left zone is smoothly normalized to 0 and 128, and the gray-level scale in the right zone is smoothly normalized to 128 and 255.

The experimental cases for proving the performance of LNMS are shown in Fig. 4. There are six test sceneries, including sunny, daytime, evening, cloudy, blurred, and rainy. The root mean square error (RMSE), shown below is utilized to compare the differences between two images in different testing scenarios.

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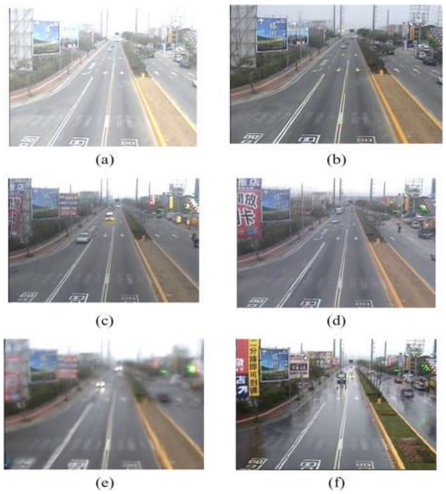

Fig. 4. Experiment scenarios for different weather conditions. (a) Sunny.(b) Daytime. (c) Evening. (d) Cloudy. (e) Blurred. (f) Rainy.

A. Dynamically Segmenting Moving Objects

GDVM is used to segment moving objects from the background. Gray road surface and white or yellow lane marks are assumptions in GDVM. The remaining colors are taken as moving objects on the road. For gray, white, and yellow, ΔRG, ΔRB, and ΔGB are small, shown below. In practical cases, most nongray cars, including white and black cars, can be segmented, shown below. To extract gray-like cars,

because the luminance Y of white cars is higher and the Y of dark cars is lower than the road surface, the Y value of the road surface always locates by excluding the range between the two threshold values. The green component G of the RGB model contributes around 60% to Y . Therefore, the G value can be adopted to reduce the computation loading, and gray-like cars can be segmented by compensating for the moving objects.

B. Detect Vehicle Candidates by Merging and Splitting Moving Objects

In practical conditions, a vehicle candidate may be broken into several moving objects in the $MO(x, y)$ domain. On the other hand, two or more closing vehicles may incorrectly be detected as one moving object. Methods of merging and splitting moving objects should be applied to more

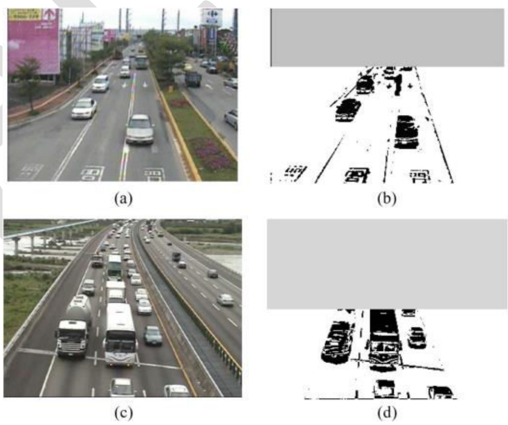

Fig. 5.Examples for applying GDVM. (a) Original image in common traffic. (b) Segmented result. (c) Original image in jams. (d) Segmented result.

precisely detect vehicle candidates. There are several steps for these methods. First, the merge boundary box rule (MBBR) is applied to merge the moving objects. The moving objects may be detected as many small rectangle boundary boxes (RBBs) in $MO(x, y)$. MBBR is a method of merging the overlapped RBBs into a large box. When two RBBs overlap, a new RBB is rebuilt to combine and replace the two old RBBs. In Fig. 6, when two RBBs, which are denoted as RBB1 and RBB2, overlap, they are merged into a new RBB, RBB4. In a recursive way, RBB5 is created by merging RBB3 and RBB4. Finally, MBBR is stopped when all overlapped RBBs are merged. After applying MBBR, fractal moving objects are merged as more solid ones, as shown in

Fig. 4. There are several attributes for determining a moving object as a vehicle candidate, including the width, height, width/height ratio, and density of the moving object. When moving objects have suitable attributes, they are identified as vehicle candidates. Otherwise, they are further merged or split. If the attributes of moving objectsexceed the limit and cannot be merged or split, they are filtered as noise. These attributes of moving objects are influenced by various practical testing environments, including camera settings, image resolutions, and viewing angles. When a vehicle is broken into several moving objects, some conditions should be met. First, the adjacent moving objects should have similar width and density. Second, the two moving objects should be shown as close. Next, the new merged movingobject should have suitable attributes, including width, height, and density. Once they meet these conditions, the moving objects should be merged as a new moving object.

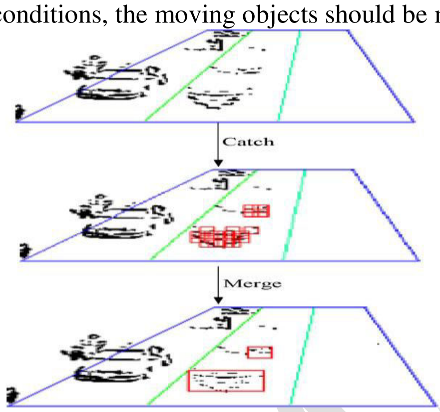

Fig. 6. Example of merging fractal moving objects by MBBR.

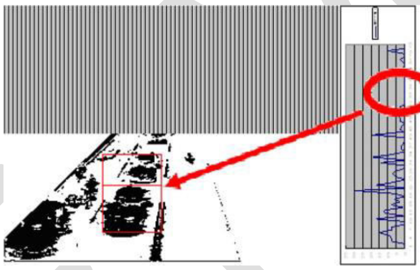

Fig. 7.Vertical projection gap between closing vehicles.

When two vehicles are too close and are mismerged as one moving object, they should be split into two or more moving objects. The steps for detecting and resolving the mismerged moving objects are listed as follows:

Step 1. Check if the moving object is a mismerged moving object. A mismerged moving object has improperly large height H, width W, H/W ratio, and density. If it is a mismerged moving object, go to step 2. If it is not amismerged moving object, the step is terminated for the moving object. Step 2. Find the gap in the vertical histogram projection of the moving object in Fig. 8. First, a low-pass filter, shown below, is applied to the vertical histogram projection, where $vp(n)$ is the histogram value at n, and $vp*(n)$ is the filtered histogram value. Second, a sliding window is used to gain the sum of the vertical histogram $svp(n)$ at n with $2M + 1$ points, shown below. Next, $ssvp(n)$, shown below, which is also similar to a sliding window, is calculated based on $svp(n)$ at n. The gap position, which is denoted as $ngap$, can be derived by checking the

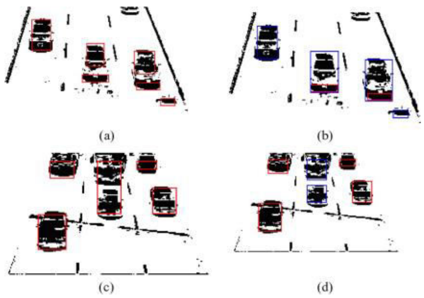

Fig. 8.Examples of merging and splitting moving objects. (a) Before mergingmoving objects. (b) After merging moving objects. (c) Before splitting movingobjects. (d) After splitting moving objects.

Fig. 8 shows an example of merging and splitting moving objects. In Fig. 8(a), the vehicle in the middle lane is misrecognized as two moving objects. They are merged as one vehicle candidate, as shown in Fig. 8(b).In Fig. 8(c), the vehicles in the middle lane are misrecognized as one moving object. They are split into two vehicle candidates, as shown in Fig. 8(d).

C. Track Vehicles With Error Compensation andUpdate Traffic Parameters

Before applying the tracking procedure, a lane mask that was automatically built through our prior studyis shown in Fig. 9(a). Meaningful traffic parameters can be updated based on the detection of the lane mask. In addition, the data structure of a tracking target should be well defined for collecting the traffic parameters. These attributes, as shown in Fig. 9(b), are listed as follows.

1) ***Coordinates of the left-bottom PLB and the right-top PRT .***
The width *W*, height *H*, and gravity *PG* of thetracked target can be gained by calculating *PLB* and *PRT*.

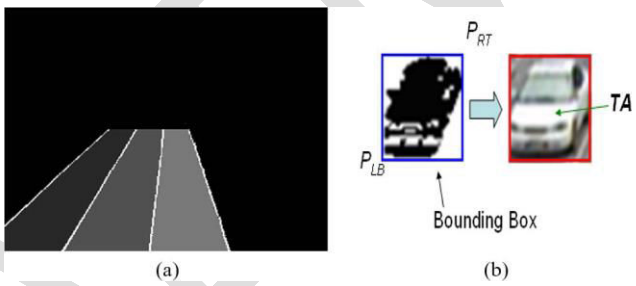

Fig. 9.Setting for tracking targets. (a) Lane masks built.
(b) Attributes of tracked targets.

In Fig. 10(b), the vehicle in the rectangle is misdetected, and the predicted position does not leave the ROI; hence, the missing vehicle will be re-searched in the blue rectangle, as shown in Fig. 10(c).

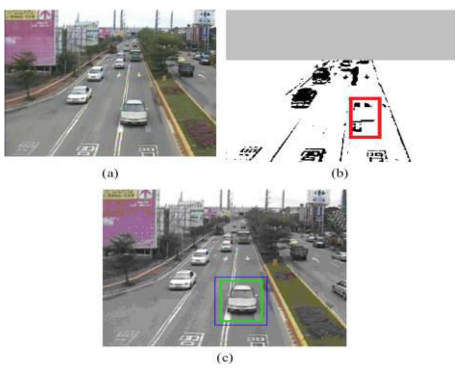

Fig. 10.Examples of the error compensation procedure.
(a) Original image.(b) Vehicle is misdetected. (c) Re-searching the vehicle in the original image.

In Fig. 10(c), the green rectangle is the predicted carsize, and the blue rectangle is the searching zone. If searchingstill fails, the target data will be updated with the latest predictingdata. If the targets miss tracking more than three times, theywill be removed from the tracking lists.Vehicle classification plays an important role in the evaluationof traffic parameters. There are two types of vehicleclassifications. The first type involves large vehicles, includingbuses and trucks, and the second type considers small vehicles,including sedans and vans. The determinants for small cars, shown below. If a vehicle satisfies the conditions, it will be recognized as a small car;

IV. EXPERIMENTAL RESULTS

To analyze the performance of the proposed methods, we must prepare several scenarios in complex environments and in different road sections, including the highway and urban sections. These scenarios are tested on Windows XP platform with a Pentium 4 2.8-GHz central processing unit (CPU), 2-GB random access memory (RAM). The size of each image is 320 × 240, and the sampling rate of the sequence is 30 ft/s. There are four parts in the experimental results. Analyses for detecting vehicles with and without error compensation methods are addressed in Part A. Parts B and C show the accuracy ratios for velocity and vehicle classification. Finally, a comparison with other methods is presented in Part D. Testing scenarios are shown in Fig. 11. In Fig. 11(a) and (b), there are two different weather conditions: One is sunny, and the other is cloudy. Fig. 11(c) shows vehicles moving at high speed with heavy shadow effects in the highway. The rainy condition is tested in Fig. 11(d). One of the tougher test cases is presented in Fig. 11(e). Vehicles moving at night are detected in this case. Finally, test cases in traffic jams are shown in Fig. 11(g). where*HC* is the setting height of the camera, $\theta C$is the view angle, *VM* is the average velocity for each car during testing, and *TAP* is the average processing time per frame. The average processing time per frame with a resolution of 320 × 240 in various environments is less than 13 ms, which achieves a frame rate of 76. In a real-time constraint, the processing time per frame does not exceed 50%of the CPU time. It indicates that the proposed system works well in real time.

The detection ratios of the first two scenarios are similar and high. Based on the results, it can be noted that the weather effects can smoothly be overcome after applying HE. In scenario (c), we can see that the background in highway is simpler than in urban setting. The test result has a higher detection ratio in this case than in the urban. In scenario (d), it can be noted that the detection ratio in the rainy condition can achieve around 85% without error compensation. After applying the error compensation procedure, the detection ratio can rise to 93%. In addition, the detection ratio at night can only reach around 82%. Again, the error compensation can reach the ratio to 93.7%. These two test scenarios are found to have lower detection ratios without the application of the error compensation procedure.

Fig. 11.Testing scenarios in various conditions. (a) Sunny day. (b) Cloudyday. (c) Shadow effects. (d) Rainy day. (e) Nighttime.
(f) Heavy traffic on ahighway. (g) Traffic jams in urban setting.

A. Analyses of Vehicle Detection and False Alarm

Finally, the results of the two traffic jam scenarios are presented, and they show that the proposed system can do well in traffic jam conditions, particularly on highways. The experimental results of the false alarm. A detected vehicle should satisfy the tracking procedure shown in Fig. 11; therefore, the false alarms seldom appear in the proposed system. However, few false alarms, including reels or large trunks, may be misrecognized as two vehicles in some cases. Fig. 12 is an example of a false alarm induced by a large trunk. Based on the experimental results, the proposed method has low false-alarm counts (FAC) and false-alarm ratios (FAR) in most scenarios. At night, vehicle-light effects will induce some FARs. In addition, more false alarms, including reels and large trunks, may appear in the highway; therefore, the FAR will slightly be impacted. In the highway, reels and large trunks are not allowed to move in the right lane, therefore, the most false detections appear in the left and middle lanes.

Fig. 12. Large trunk induces false-alarm detection.

B. Accuracy Ratio of Vehicle Velocity

Experimental results for the detection of vehicle velocity are shown. The initial velocity of the tracking target is calculated from the change in gravity. Then, the average velocity, which is denoted as *VM*. The reference velocity is detected by the velocity-detection radar. The tolerance is set to ±5 km/h. If the difference between the velocity detected by the proposed system and the velocity detected by radar is lower than the tolerance, the velocity can be thought to be correct. There are two types of accuracyratios are calculated. One type is based on the total target count(TTC), which will be affected by the detection ratios. The other type is based on the detected count(DC), and the detection ratios are higher than the former type.

Based on the results, the detection ratios ofvelocity are high in most cases. In scenario (e), the detection ratio is lower than other cases,because the light effects greatly influence size detection andgravity position. In the traffic jam case in scenario(g), vehicles move slowly and suddenly stop for the traffic light.Therefore, the velocities in this case heavily vibrate, and theaccuracy ratio is lower than other cases.

V. CONCLUSION:

In this paper, an adaptive vehicle detection approach for complex environments has been presented. This paper has also proposed methods for solving vehicle tracking in traffic jamsand complex weather conditions, such as sunny, rain, sunrise, sunset, cloudy, or snowy days. HE is used to remove the effects of weather and light impact. The method is applied to improve the tracking accuracy ratio and simplify the system parameter settings. GDVM is used to dynamically segment moving objects. Finally, tracking and predict compensation are applied to refine the target tracking quality. Based on the experimental results, the data indicate that the tracking accuracy ratio of the proposed system is quite good in traffic jams and complex weather conditions, particularly when applying the error compensation procedure. In the comparisons with other approaches, the proposed method not only has higher detection ratios but gathers more useful traffic parameters as well. In addition, the proposed system can easily be set up without being given any environment information in advance. In this paper, many useful traffic parameters are built, and they can be used to control the traffic. Furthermore, this information can be combined with a personal digital assistant (PDA) or mobile phone system to provide traffic conditions for vehicle drivers. In future works, we still need to improve the accuracy ratio when it is raining and at night. In addition, the detection of motorcycles is necessary to make the system practical for commercial usage.

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